User Content Generation and Usage Behavior in Multi-media Settings: A Dynamic Structural Model of Learning[1]

Anindya Ghose
Stern School of Business, New York University, New York, New York 10012, aghose@stern.nyu.edu

Sang Pil Han
Stern School of Business, New York University, New York, New York 10012, shan2@stern.nyu.edu

Consumer adoption and usage of mobile communication and multimedia content services has been growing steadily over the past few years in many countries around the world. In this paper, we develop and estimate a dynamic structural model of user behavior and learning with regard to content generation and usage activities in mobile multi-media environments. We model that users make content choices based on how well the content matches their taste. Users learn about two different categories of content – content from regular Internet social networking and community (SNC) sites and that from mobile portal sites. Then they can choose to engage in the creation (uploading) and consumption (downloading) of multi-media content from these two categories of websites. In our context, users have two sources of learning about content match value – (i) direct experience through their own content creation and usage behavior and (ii) indirect experience through word-of-mouth such as the content creation and usage behavior of their social network neighbors. Our model seeks to explicitly explain the underlying mechanism of user content generation and usage in mobile multi-media settings and examine how direct and indirect experiences influence the content creation and usage behavior of users over time. We develop a dynamic structural model. We estimate this model using a unique dataset of consumers' mobile media content creation and usage behavior over a 3-month time period. Our estimates suggest that when it comes to user learning from direct experience, the content downloaded from mobile portal sites has the highest level of mean match value. In contrast, the content downloaded from Internet SNC sites has the lowest level of mean match value. In terms of the magnitude of estimates, the standard deviation of indirect experience signals is higher than the standard deviation of direct experience signals. That is, in the mobile multi-media context, learning based on direct experience is more reliable (has less variability) than learning based on indirect experience. We use our estimates to assess the importance of learning through different counterfactual experiments. Our policy simulations suggest that the impact of an increase in content match value on the propensity to download content from mobile portal sites is higher for the segment that is geographically more mobile. In contrast, the impact of an increase in content match value on the propensity to upload content to mobile portal sites is higher for the segment that is geographically less mobile. Potential implications for mobile phone operators and mobile advertisers are discussed.

Keywords: structural modeling, dynamic learning, mobile media, mobile portals, Internet websites, uploading content, downloading content, complements, dynamic programming, simulated maximum likelihood estimation.

[1]We thank Tülin Erdem for very helpful comments. We also thank Sanjeev Dewan, Russ Winer, and participants at Marketing Dynamics Conference 2009, SCECR 2009 and Marketing Science 2009 for helpful comments. Anindya Ghose acknowledges the generous financial support from NSF CAREER award (IIS-0643847). Funding for this project was also provided by a 2009 NET Institute grant and a grant from the Wharton Interactive Media Institute-Marketing Science Institute (WIMI-MSI) grant competition on user-generated content. The usual disclaimer applies.

1. Introduction

Taking cues from electronic commerce, different kinds of user-generated content (hereafter UGC) are becoming available in mobile multi-media environments as well, spurred by rapid advances in the cellular telephony market. Besides content on regular websites and social networking sites, other examples of content created and accessed through mobile phones include photos, graphics, ring tones, videos, podcasts, and other kinds of multi-media content. As of today, several content management systems and social media platforms have created lightweight versions of their hosted sites automatically for users that come in via a mobile phones or WAP (Wireless Application Protocol) browsers. This process has facilitated increased user adoption of mobile commerce. Increasingly, we see more and more companies and mainstream brands launching a mobile web presence so they can engage directly with their consumers. A recent study reports that about 10% of mobile Web users have made a purchase based on a mobile ad, 23% have visited a Web site, and 13% have requested more information about a product or service (OPA News 2007). Further, mobile portal sites that combine social networking and user-generated content are establishing large user bases and monetizing content via advertising (Chard 2008).

In many countries, a unique aspect of the mobile multi-media services is that users need to explicitly incur expenses (for example, by paying data transmission charges) during their mobile content generation and usage endeavors based on the number of bytes uploaded or downloaded. This is in contrast to electronic commerce where content usage and generation on blogs and opinion forums through a PC or laptop using an Internet connection (broadband or DSL) can be done without incurring any additional variable costs over and above the fixed monthly usage fees. With mobile phones becoming an increasingly significant medium for Internet access, mobile operators' portals offer an innovative and differentiated route for advertisers to reach users. Therefore, understanding what kinds of websites users access using their mobile phones is key towards examining their potential as an advertising medium.

In this paper, we develop and estimate a dynamic structural model of users' content generation and usage activities in a mobile multi-media setting. Our data has explicit information on the two most frequently visited categories of websites that users can access through their cell phones – regular Internet social networking and community-oriented (SNC) sites and mobile portal sites (more information on these two categories is provided in the 'Data' section). This distinction is important because of the fundamental differences in the operation of mobile portal sites from regular websites. Mobile portal sites are owned and hosted by mobile phone companies. Examples include Vodafone live, T-Mobile's Web'n'Walk, Planet3, Orange World and O2 Active. Some of the content on these sites comes from third-party content creators who have entered into contracts with mobile phone operators. As a result, mobile operators have better control on the kind and quality of content that is available on these websites.

This is as opposed to regular Internet websites where mobile phone operators can exercise less control on the content that is available for obvious reasons. Hence, an understanding of differences in user behavior (uploading and downloading content) between mobile portal sites and regular social networking and community (SNC, hereafter) websites can be useful from the point of view of monetization of UGC through mobile advertising.

The context of our empirical analysis is akin to that of user dynamics and learning in experience goods. We model user behavior and learning with respect to two different categories of content – content from SNC sites and content from mobile portal sites and with respect to two different kinds of activities – content creation (uploading) and consumption (downloading). We do so in a dynamic structural model setting with Bayesian updating.[2] In our context, there are several reasons why user behavior might exhibit dynamics. First, as is known in the prior literature on state dependencies, choices made in previous periods might causally affect a user's current period utility and behavior. Second, as is known from the work on habit persistence there are temporal dependences in the random component of utility users derive from products (Heckman 1981). Third, users can exhibit forward-looking behavior in which they maximize the stream of expected utilities over a planning horizon rather than maximizing their immediate utility. As an example, current choices might depend on their information value and their impact on future utility, like in strategic consumer trial or sampling behavior (Eckstein et al. 1988). If this were so, then decision makers need to take into account the impact of their current actions on their future stream of utilities.

In fact, there is evidence of user dynamics in mobile multi-media content settings. Specifically, prior work has shown that there are positive state dependencies in the content generation and content usage behavior of the users in mobile multi-media settings (Ghose and Han 2009). In addition, we have seen a positive association between the behavior of social network neighbors and the content generation and content usage behavior of a user in our prior work (Ghose and Han 2009). However, existing work does not model how and why users' current choices depend on past choices. Nor does it explain the underlying mechanism of how and why one's choices depend on the choices of their social network neighbors.

Furthermore, user uncertainty can arise in situations with imperfect information about product characteristics and in fast-changing environments. Under uncertainty, past experience with brands (products) as well as marketing mix elements may affect a consumer's information set, which in turn

[2] There are a couple of reasons why we choose to adopt such an approach. First, incorporating user dynamics into structural econometric models can enhance our understanding of user behavior. A dynamic structural approach takes into account the fact that when current choices influence future pay-offs, and hence the behavior of a rational decision-maker must be forward-looking (Chintagunta et al. 2006). Second, dynamic structural models may be able to explain certain empirical patterns that are not captured by static models especially when it comes to situation involving uncertainty and learning. Hence, ignoring the dynamics could potentially "throw away" valuable information and in the worst case could generate misleading conclusions about behavior (Chintagunta et al. 2006).

affects his/her current choices (Erdem and Keane 1996). It is easy to see how there can be uncertainty and learning incentives in a mobile multi-media setting. Users can be uncertain about the benefits from spending time and monetary resources towards content generation and content usage activities. Further, they may lack information about the benefits from content generation and usage at the specific content category level. For example, downloading audio files from mobile portal sites can provide information about the direct benefit from audio content but provide little information about the utility from downloading other types of content (such as video files) from SNC sites. Similarly, users may be uncertain about the taste matching possibility with each content activity. For example, uploading a photo to SNC sites may appeal more to younger users, while downloading an audio file from a mobile portal site may appeal more to older users. Finally, there are additional preferences matching or quality-signaling mechanisms in our context, which could facilitate reduce uncertainty and facilitate learning – such as the behavior of social network neighbors.

These reasons suggest that a dynamic structural model of user learning is well suited for our context. Our paper builds and estimates a structural model of user behavior in which forward-looking users learn about how well a particular content activity matches their 'taste'. We also analyze a competing model in which consumer behavior is dictated by user-invariant true content quality. The learning in either model (content taste or content quality associated with each activity) occurs through direct signals such as their own content creation and usage behavior as well as through indirect word-of-mouth (WOM) signals such as the content creation and usage behavior of their social network neighbors. Hence, our model seeks to explicitly explain how direct experience from previous own content creation and usage and indirect experience from social interactions affect the content creation and usage behavior of users over time.

We find that "content match value" model better explains than "content quality model" in both in-sample and out-of-sample data. Our parameter estimates from the content match value model suggest that there is substantial heterogeneity in the mean content match value across different content types. Downloads from mobile portal sites have the highest mean match value level, followed by upload to mobile portal sites, upload to SNC sites and download from SNC sites. In addition, we find that, in terms of magnitude of estimates, the standard deviation of indirect experience signals is generally higher than the standard deviation of direct experience signals. That is, in the mobile media context, learning based on direct experience is more reliable (has less variability) than learning based on indirect experience. Our policy simulations suggest that the impact of an increase in mean match value on the propensity to download content from mobile portal sites is higher in the segment that exhibits a higher level of geographic mobility (based on the number of unique locations from where calls are made). In contrast, the impact of an increase in content match value on the propensity to upload content to mobile portal sites is higher for the segment that is less geographically mobile. Furthermore, the mean match value and user taste heterogeneity can act as complements in activities involving content upload to SNC sites and content upload to mobile portal sites.

To summarize, the key contributions of this paper are the following. *First*, it addresses a key question unexplored in the emerging stream of literature in the economics of user-generated content: how users learn the match value with mobile multi-media content (both content generation and usage activities) from the two most frequently visited categories of websites – (i) Internet social networking and community sites and (ii) mobile portal sites. *Second*, it develops a structural framework of user content generation and usage and tests two competing models - a “content match value” model in the spirit of Crawford and Shum (2005) and a “content quality” model in the spirit of Erdem et al. (2008). The content match value model is based on the notion that certain kinds of content may appeal more to certain user groups. In contrast, the content quality model is based on the notion that there is a true quality value for each content type and the perceived quality of some content is the same across users. We find evidence that in the context of mobile multi-media, users make choices based on their perception of differences in content taste rather than content quality. *Third*, it distinguishes between the effects of two different sources of learning (i.e., direct experience and indirect word-of-mouth experience) on user behavior, and finds evidence for both. We do this by using a novel panel dataset encompassing individual user-level mobile activity information, the same users’ social network information, and the mobile activity information of network neighbors (peers). We develop a complex modeling procedure for value function derivation and simulation-based estimation. To our knowledge, no prior research using structural modeling has employed an individual-level word-of-mouth interactions data among users to capture the indirect source of learning in consumer behavior. *Finally*, we run a series of policy simulations and discusses managerial implications for targeting and advertising strategies for mobile service providers. These implications shed light on the monetization potential of user generated content in mobile multi-media.

The rest of this paper is organized as follows. Section 2 outlines the prior work in related areas. In Section 3, we provide the theoretical framework for the structural model. This includes information on user decision-making process, description of the utility specification with posterior mean and variance, the formulation of the dynamic optimization problem and econometric estimation. Section 4 describes the data that we deploy with some summary statistics that provide interesting insights into user behavior. We describe the key results in Section 5 and discuss an extension to the main model in which consumers choose content-related activities based on their perceived benefit from the quality associated with that activity as opposed to how well a specific content-related activity matches their taste preferences. Section 6 presents results from various policy simulations. Section 7 discusses implications and concludes.

2. Prior literature

A number of recent papers have developed dynamic structural demand estimation models. The main focus of prior work has been on modeling direct learning and too in the context of durable or storable goods (Erdem and Keane 1996 , Hendel and Nevo 2006, Gowrisankaran and Rysman 2007, Ching and Ishihara 2009). There is also existing work in the domain of nondurable experience-goods markets (for example, Ackerberg 2001, Israel 2005, Crawford and Shum 2005, Erdem et al. 2008) of which the latter two papers are most closely related to our work. Crawford and Shum (2005) look at learning from direct experience such as symptomatic signals and curative signals of drugs in a pharmaceutical industry. Erdem et al. (2008) incorporate user experience, advertising content, advertising intensity, and price as signals of product quality in a learning model in a product category like ketchup. However, none of these papers consider the possibility of any kind of indirect learning through explicit word-of-mouth (WOM) interactions.

Erdem et al. (2005) look at consumers' active learning in a fast-changing market (e.g., computers) and develop a structural model of consumers' decisions about how much information to gather prior to making a purchase. However, they employed survey data where they asked subjects about the source of information without using the actual communication history between consumers or the strength of the WOM communications. Iyengar et al. (2007) look at a wireless service industry and model the dual learning process of service provider's quality and consumer's consumption quantity within a Bayesian learning framework. Narayanan et al. (2005) propose a Bayesian learning process model that incorporates the impact of direct (perceived product quality) and indirect (through goodwill accumulation) effects on consumer utility in the context of physician learning for new drugs. We also incorporate the effect of social network neighbors on users' content generation and usage behavior. A small but growing number of papers have investigated peer effects in new product adoption (Van den Bulte and Lilien 2001, Manchanda et al. 2004), and Iyengar et al. (2008) in drug adoption and Nam et al. (2006) in video-on-demand adoption. Nair et al. (2008) document the presence of asymmetric social interactions. See Hartmann et al. (2008) for a comprehensive survey of the social interactions literature. However, these papers do not analyze learning with respect to content creation and usage behaviors in the mobile multi-media setting nor do they distinguish the *indirect WOM* effect from the *direct usage* effect, as we do in this paper.

Finally, our work is also related to the stream of literature on the economic impact of user-generated content (UGC). Studies have used the numeric review ratings (e.g., the number of stars) and the volume of reviews in their empirical analyses (Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Forman et al. 2008, Duan et al. 2008) as well as tested whether the textual information embedded in online UGC can have an economic impact (Ghose et al. 2005, Ghose and Ipeirotis 2008, Das and Chen 2007, Archak et al.

2008, Ghose 2009) using automated text mining techniques. Related to this stream of work, Trusov et al. (2008) find that in an online world, if an influential member in a social networking site creates content, then the people connected to him or her increase their content usage. Our paper is distinct from all of the above in that we consider the content generation and usage behavior in a multi-media context as opposed to one consisting of only numeric or textual content.

In summary, there are two aspects we aim to address in our paper: a dynamic structural model of user learning about content match value in a Bayesian manner, and users' dynamic learning about content match value based on their own behavior as well as from indirect WOM experience of their network neighbors. Whereas previous work has examined some of these issues separately, we address these aspects together. The Bayesian learning-based structural model gives a different picture of the value of information than would be obtained by simply estimating a static discrete choice model. This is because the Bayesian learning-based model incorporates the fact that information from either of the two sources can be valuable by inducing people to switch choices, and thus both positive and negative signals are valuable. Moreover, our study is in the context of multi-media content access and creation through mobile phones, which has not been explored, in prior work.

3. Model

We model user behavior in an environment where users are uncertain about the "match value" of content that is being consumed or generated through mobile phones and attempt to learn about it. There are two sources that can shape a consumer's evaluation: own consumption behavior, which we refer to as the direct effect, and the consumption behavior of their network neighbors, which we refer to as the word-of-mouth, *or indirect effect*. Users may be risk averse with respect to variation in content match value. This is reasonable to assume in a context where sampling is costly since users need to pay transmission charges based on the amount of traffic that is being downloaded or uploaded. We first start with the discussion of the content match value model. The analysis with respect to the model on content quality is examined in Section 5 while the actual technical details are relegated to the Appendix.

We adopt a single agent, dynamic discrete choice framework. A user's objective is to determine an optimal sequence of content generation and usage choices. Users update their expectations in a Bayesian manner as they receive additional signals of content match value. We set our time period of analysis to be a 'day.' Posterior beliefs are updated once at the end of each day. This helps us synchronize the incidence timing of two sources of information that can influence their behavior and learning – direct experience and indirect experience.

In our paper, we focus on distinguishing between the two broad classes of websites described before. Hence, in order to model the set of user choices, we allow users to choose amongst the following five distinct options: (i) upload content to Internet SNC sites, (ii) upload content to mobile portal sites, (iii) download content from Internet SNC sites, (iv) download content from mobile portal sites, and (v) doing nothing.

We model users' information set and choice timings as follows. Based on users' own prior experiences and the information they have received from their social networks, they start with a pair of prior beliefs about each activity at the beginning of day *t*. Users receive activity-specific information from their social networks through day *t*.[3] Then they calculate the choice-specific value using their value functions, evaluate their choices amongst the various alternatives, and choose the one with the highest value. Thereafter, users update their posterior on perceived content match value from their own usage experience as well as that of their social networks at the end of day *t*.

3.1 User Decision and Content Match Value Uncertainty

A user *i* can engage in a given content activity *j* as many as *s* events on day *t*. Since users are forward-looking in our model, their current choices can influence their preferences in future periods. Hence, they select the sequence of choices that maximizes their expected utility over an infinite time horizon. We specify user *i*'s expected utility as follows:

$$\max_{D \equiv \left\{ \left\{ \left\{ d_{ijt}^{s} \right\}_{j=1}^{J} \right\}_{s=1}^{N_{Sit}} \right\}_{t=1}^{\infty}} E_D \left(\sum_{t=1}^{\infty} \beta^t \sum_{s=1}^{N_{it}} d_{ijt}^{s} U_{ijt}^{s} \right) \tag{1}$$

where $j \in \{1$ = upload to SNC sites, 2 = upload to mobile portal sites, 3 = download from SNC sites, 4 = download from mobile portal sites and 5 = doing nothing$\}$, N_{it} is the number of times user *i* is involved in an activity on day *t*, β is a discount factor, d_{ijt}^{s} denotes 1 if user *i* chooses activity *j* at the s^{th} event on day *t* and 0 otherwise, and U_{ijt}^{s} denotes the associated utility.

We consider a setting where certain content characteristics may appeal more to certain user groups. In this setting, user *i* has an idiosyncratic match value with activity *j*. Users are imperfectly informed and thus uncertain about the match value with each of the four kinds of activities, similar in spirit to prior work (Crawford and Shum 2005). User experiences with respect to content match value vary. We model this as follows:

$$M_{ij} \sim N\left(M_j, \sigma_{M_j}^2\right). \tag{2}$$

[3] In order to incorporate the impact of indirect signals from network neighbors and the associated communication strength of each signal, we fix the maximum number of network neighbors for each user to five based on the call frequencies between them. The qualitative nature of our results is robust to the use of other numbers as well ranging from one to five. It is also robust to the use of call duration (rather than call frequency) to determine the social network, for a given user.

M_j is the population mean match value of activity *j* and $\sigma^2_{M_j}$ measures the extent of the heterogeneity for content match values across users with respect to activity *j*. The values M_j and $\sigma^2_{M_j}$ are assumed to be known by users and are parameters to be estimated.

We posit that the direct experience provides an unbiased signal of an idiosyncratic, user-specific "match value" with each activity as follows:

$$M^s_{Eijt} = M_{ij} + \zeta^s_{ijt} \qquad \text{where} \qquad \zeta^s_{ijt} \sim N\left(0, \sigma^2_{\zeta j}\right). \tag{3}$$

That is, $M^s_{Eijt} \sim N\left(M_{ij}, \sigma^2_{\zeta j}\right)$.

In addition to variation in the direct experiences of users, there can be variation in the indirect experiences of users. This can happen because the network neighbors of a user, like the users themselves, receive a noisy signal of idiosyncratic, their own content match value from the upload and download activities across both the kinds of websites. Moreover, when the information regarding content match value is transferred via (say) word-of-mouth, there could be additional sources of noises such as incorrect delivery of the information by a sender, misunderstanding by a recipient, etc. Hence, to allow for this possibility, we model the information from network neighbors as providing a noisy but unbiased signal of population mean match value of each activity. Further a complication arises from the fact that users can receive multiple indirect experience signals on a given day. We assume that each user receives indirect experience signals only from those network neighbors who have experienced it in that period. We denote the indirect experience signal of user *i* from a network neighbor *k* who has participated in activity *j* on the same day *t* as follows:

$$M^f_{WOMijt} = M_j + \eta^f_{ijt} \tag{4}$$

where

$$\delta^f_{ijt} \sim N\left(0, \sigma^2_{\eta j}\right),$$

$$f \in N_{WOMijt} = \sum_{k \in n_i} \sum_{h=1}^{N_{Ekjt}} w_{ik} d^h_{kjt}.$$

We refer to $\sigma^2_{\eta j}$ as the "choice-specific indirect experience variability." Because own experience is likely to provide a less noisy signal of the match value of a given activity than indirect experience, we expect that $\sigma^2_{\eta j} \geq \sigma^2_{\zeta j}$ for each activity *j*.

We posit that we can derive N_{WOMijt} by computing the weighted count of frequency of engaging in each activity by user *i*'s network neighbors. Specifically, to incorporate the communication intensity between users, we use voice call frequency as a weight. This is motivated by the possibility that higher the number of voice calls between a caller and a receiver, higher the probability of receipt of an indirect experience signal with respect to activity *j* by that user, given that the receiver engaged in that activity on the same day. Thus, user *i* receives $\sum_{k\in n_i}\sum_{h=1}^{N_{Ekjt}} w_{ik} d_{kjt}^{h}$ indirect experience signals from network neighbors on day *t*. Here w_{ik} is *relative* call frequency between user *i* and user *k* (who is a network neighbor of user *i*) and d_{kjt}^{h} is an indicator variable indicating whether or not user *k* engaged in activity *j* at h^{th} event on day *t*.[4]

3.2 User Utility Function

Let U_{ijt}^{s} denote user *i*'s single-period utility from activity *j* at s^{th} event on day *t*. Let M_{Eijt}^{s} denote user *i*'s match value signal from directly experiencing content activity *j* at s^{th} event on day *t*. This follows from the fact that utility is a function of experienced attribute levels and not the mean attribute levels (Erdem and Keane 1996). p_j is the average price of activity *j*. We posit that users are risk averse with their utility being concave in content match value and linear in price. Similar in spirit to Erdem et al. (2008), we assume users have a per-period utility function of the form, for activity *j* = 1,..., 4:

$$U_{ijt}^{s} = w_g * M_{Eijt}^{s} + w_g * r_g * \left(M_{Eijt}^{s}\right)^2 - a_g * P_j + \varepsilon_{ijt}^{s}. \tag{5}$$

Subscript *g* denotes the number of latent segments. Note that *w* is user *i*'s utility weight on content match value, *r* captures the extent of the risk aversion towards variation in match value (*r* < 0: utility is concave, so the user is risk averse), *a* is the price coefficient, and ε_{ijt}^{s} captures a taste shock known to user *i* but not to the researcher. We note that a set of state variables I_{it} includes all signals that user *i* received through day *t*. Then, letting $\mu_{ij,t} \equiv E[M_{ij}|I_{it}]$ denote user *i*'s expectation of activity *j*'s match value level on day *t*, we re-write Equation (2) as follows:

$$M_{Eijt}^{s} = \mu_{ij,t} + \left(M_{ij} - \mu_{ij,t}\right) + \eta_{ijt}^{s}. \tag{6}$$

Then, based on Equation (5), the expected utility to user *i* from choosing activity *j* on day *t* given state variables I_{it} is given as follows:

$$E[U_{ijt}^{s}|I_{it}] = w_g * \mu_{ij,t} + w_g * r_g * \left(\mu_{ij,t}\right)^2 + w_g * r_g * E\left[\left(M_j - \mu_{ij,t}\right)^2|I_{it}\right] + w_g * r_g * \sigma_\eta^2$$
$$-a_g * P_j + \varepsilon_{ijt}^{s}. \tag{7}$$

[4] For example, suppose that user A has 3 network neighbors who engaged in activity 1 on a given day. Suppose they engaged four, five and two times, respectively in this activity. Further, suppose that user A made calls to each other the network neighbor 4, 2, and 10 times on that day, thus the weight of the intensity of communication of user A with each of these network neighbors is 4/16, 2/16, and 10/16, respectively. Then the count of number of times user A receives indirect signals about content activity 1 is computed as (4/16) x 4 + (2/16) x 5 + (10/16) x 2 = 2.875.

There are two sources of expected variability in direct experience match value, M_{Eijt}. First is the experience variability, σ^2_{η}. Second is the variability of actual match value around perceived match value, $E\left[\left(M_{ij}-\mu_{ij,t}\right)^2|I_{it}\right]$. That is, if a user has little information about the activity or about one's preference about the activity, then the actual match value will tend to depart somewhat from expected match value, and thus the term is large. In addition, we simply assume that the expected utility associated with "doing nothing" to be a constant plus a stochastic error component as follows:

$$E[U_{i5t}|I_{it}] = \varphi_0 + \varepsilon_{i5t}, \tag{8}$$

3.3 Users Updating Perceived Content Match Value

Users have prior beliefs about the "mean" match values for each activity *j* at the beginning of the pre-estimation sample. That is, users have a mean match value of M_0 but the match value of activity *j* has variance $\sigma^2_{M_0}$. Following Erdem et al. (2008), we restrict the prior mean M_0 to be equal to the mean of the all activity-specific population mean match value M_j for *j* = 1,..., 4.[5]

User *i* does not know the match value with of any of the four possible options, but receives signals, which allow that user to update his perceived match value with activity *j* from direct experience as well as indirect experience of his network neighbors. Note that user *i* may receive multiple content match value signals at time *t* as many as N_{WOMijt} times.

In terms of the updating process, we assume that users use information (i.e., either the direct experience signal or the indirect experience signal, or both) that they receive over time. To be specific, they learn about the mean and variance of match values in a Bayesian fashion (DeGroot 1970) according to the process described below in (a) and (b).

(a) Posterior Mean of Perceived Content Match Value

Unlike cases where there is only one signal per a source at a given time (e.g., Crawford and Shum 2005, Erdem et al. 2008), in the mobile multi-media context users can receive *multiple* signals of direct and indirect experience on a day. This is because in a mobile multi-media context, users create and consume content far more frequently compared to products like computers and drugs. This setting is, in spirit, similar to Mehta et al. (2008). Moreover, in our setting they communicate more frequently with friends and colleagues so that opinions or ideas about one's experience are more likely to be shared with each other. To address the modeling complication arising from this, we posit that although users can

[5] We also model an alternative setting where users have idiosyncratic "match values" to each activity *j*. As a robustness check, we discuss the result in Section 5.

receive multiple match value signals within a day, they update their posterior beliefs once at the end of a day.

Let the posterior mean of perceived match value with activity *j* on day *t*+1 be denoted as $\mu_{ij,t+1}$. At the end of day *t*+1, the posterior mean can be written as the sum of three separate components - (i) prior mean at the end of day *t*, (ii) sample mean of the realized match value signals from direct experience during day *t*+1, and (iii) sample mean of the realized match value signals from indirect experience during day *t*+1. This is written as follows:

$$\mu_{ij,t+1} = \left(\beta_{1ij}^{t+1} * \mu_{ij,t}\right) + \left(\beta_{2ij}^{t+1} * \overline{M_{Eijt+1}}\right) + \left(\beta_{3ij}^{t+1} * \overline{M_{WOMijt+1}}\right) \tag{9}$$

where

$$\overline{M_{Eijt+1}} = \frac{1}{N_{Eijt}} \sum_{s=1}^{N_{Eijt}} M_{Eijt+1}^{s},$$

$$\overline{M_{WOMijt+1}} = \frac{1}{N_{WOMijt}} \sum_{f=1}^{N_{WOMijt}} M_{WOMijt+1}^{f},$$

$$\beta_{1ij}^{t+1} = \frac{\frac{1}{\sigma_{M_{ij,t+1}}^{2}}}{\frac{1}{\sigma_{M_{ij,t+1}}^{2}} + \frac{N_{Eijt}}{\sigma_{\zeta j}^{2}} + \frac{N_{WOMijt}}{\sigma_{\eta j}^{2}}},$$

$$\beta_{2ij}^{t+1} = \frac{\frac{N_{Eijt}}{\sigma_{\zeta j}^{2}}}{\frac{1}{\sigma_{M_{ij,t+1}}^{2}} + \frac{N_{Eijt}}{\sigma_{\zeta j}^{2}} + \frac{N_{WOMijt}}{\sigma_{\eta j}^{2}}}, \text{ and}$$

$$\beta_{3ij}^{t+1} = \frac{\frac{N_{WOMijt}}{\sigma_{\eta j}^{2}}}{\frac{1}{\sigma_{M_{ij,t+1}}^{2}} + \frac{N_{Eijt}}{\sigma_{\zeta j}^{2}} + \frac{N_{WOMijt}}{\sigma_{\eta j}^{2}}}. \tag{10}$$

The intuition behind the above updating Equation (9) is that the posterior mean of perceived match value at the end of day *t*+1 is a weighted average of the three components described above. In doing so, we consider the weight for each component by its relative accuracy. To compute the extent of relative accuracy of each signal, as shown in Equation (10), we use the inverse of variance of each source such that the less diverse a signal generated from a source, the more accurately it represents the match value. Note that $1/\text{variance}$ of a signal is equivalent to the accuracy of the signal. For example, β_{1ij}^{t+1} represents the ratio of accuracy of the prior belief to the sum of the accuracy of the prior belief, the direct experience signal, and the indirect experience signal. β_{2ij}^{t+1} represents the ratio of accuracy of the direct experience signal to the sum of the accuracy of the prior belief, the direct experience signal, and the indirect experience signal. Similarly, we can interpret β_{3ij}^{t+1}.

For simplicity, we posit that the network neighbors and the communication strength between them remain fixed throughout the sample period. This knowledge is public in the sense that the econometrician can treat this information as exogenously given. Also, $\sigma^2_{M_{ij,t+1}}$ is the variance of user *i*'s belief of activity *j*'s mean match value at time *t*+1. We explain this in the next section.

(b) Posterior Variance of Perceived Content Match Value

Let the posterior variance of perceived match value with content activity *j* on day *t*+1 be denoted by $\sigma^2_{Q_{ij,t+1}}$. We compute it according to the following. There are three components of relevance here - (i) the inverse of prior variance of perceived match value at the start of estimation sample (*t*=0), (ii) the sum of the inverse of the variance of the direct experience signals, and (iii) the sum of the inverse of the variance of the indirect experience signals. Higher the value of (ii) or (iii), lower the posterior variance implying the higher the posterior accuracy. This is written as follows:

$$\sigma^2_{M_{ij,t+1}} = \frac{1}{\frac{1}{\sigma^2_{M_{ij,o}}} + \frac{\sum_{\tau=1}^{t+1} N_{Eij\tau}}{\sigma^2_{\zeta j}} + \frac{\sum_{\tau=1}^{t+1} N_{WOMij\tau}}{\sigma^2_{\eta j}}}. \tag{11}$$

Note that N_{Eijt} denotes the count of number of times that user *i* chooses activity *j* on day *t*, and N_{WOMijt} denotes the count of number of times that user *i* receives an indirect signal about the match value with activity *j* from his network neighbors on day *t*.

(c) Specifying Initial Conditions

We account for the well-known "initial conditions" problem in our model because for each user the first observation in our sample may not be the true initial outcome of his/her mobile content generation and usage behavior. The initial conditions issue has implications for what we assume about the prior mean and variance of the match value perceptions. If one does not control for initial choice history, the implicit assumption is that every user has the same prior mean and variance across all content types. However, it is possible that a user that has engaged in an activity multiple times in the past would have more informed priors than another user who has engaged very little in that activity. Hence, one needs to account for the heterogeneity of priors in the sample.

Table 1. Notations and Variable Descriptions

β	discount factor
M_{ij}	user i's match value with activity *j*
N_{it}	count of the number of times user *i* is involved in content choices on day *t*
d_{ijt}^{s}	whether user *i* chooses activity *j* at *s*th event on day *t* (1 = Yes, 0 = No)
U_{ijt}^{s}	user *i*'s immediate utility from activity *j* at *s*th event on day *t*
N_{Eijt}	count of number of times that user *i* engages in activity *j* on day *t*
Q_{Eijt}^{s}	user *i*'s received direct experience match value signal about activity *j* at *s*th event on day *t*
N_{WOMijt}	count of number of times that user *i* receives indirect signal about content activity *j* from his or her network neighbors on day *t*
n_i	user *i*'s network neighbors based on voice call records (i.e., users called by user *i*)
Q_{WOMijt}	user i's received indirect word-of-mouth match value signal about activity *j* on day *t* from network neighbors
$\sigma_{\zeta j}^{2}$	Variance of the direct experience signal of activity *j*
$\sigma_{\eta j}^{2}$	Variance of the indirect experience signal of activity *j*
w_g	weight on content match value for *g*th latent segment
r_g	extent of risk aversion towards variation in match value for *g*th latent segment
a_g	weight on price for *g*th latent segment
P_j	average price of activity *j*
M_0	mean of the all activity-specific match value levels
$\mu_{ij,t}$	user *i*'s posterior mean of perceived match value about activity *j* on day *t*
w_{ik}	tie strength between user *i* and user *k* who is a network neighbor of user *i* based on call frequencies therein
k_0	initial condition parameter; log of prior standard deviation at the beginning of the pre-estimation sample
k_1	initial condition parameter; the impact of cumulative experiences in the pre-estimation sample period on prior variance at the start of estimation sample period
$\sigma_{M_0}^{2}$	user *i*'s prior variance of perceived match value at the beginning of pre-estimation period (*t*<0)
$\sigma_{M_{ij,0}}^{2}$	user *i*'s prior variance of perceived match value at the end of pre-estimation period (*t*=0)
$\sigma_{M_{ij,t}}^{2}$	user *i*'s posterior variance of perceived match value about activity *j* on day *t (t>0)*
I_{it}	user *i*'s state variables on day *t*
l_{ij}^{t}	count of number of times that user *i* has done activity *j* up to and through day *t*
m_{ij}^{t}	count of number of times that network neighbors of user *i* have engaged in activity *j* up to and through day *t*
V_{it}	user *i*'s value function on day *t*
$\bar{V}$	user *i*'s integrated value function on day *t*
V_{ijt}	user *i*'s choice-specific value function on day *t*

We follow an approach that is similar in spirit to that used in Erdem et al. (2006) and Mehta et al. (2008) and use a part of the data as a pre-estimation sample to estimate the distribution of priors. Because our data contain social network data only for the last 35 days (5 weeks), we use first 56 days (8 weeks) to estimate each user's initial conditions and the last 35 days to estimate the model. We posit that user *i*'s prior standard deviation of the match value level with activity *j* at the start of our estimation period is as follows:

$$\ln\sigma_{M_{ij,0}} = k_0 - k_1 \sum_{t=-55}^{0} \sum_{s=1}^{N_{Eijt}} d_{ijt}^{s}, \tag{12}$$

where k_0 and k_1 are parameters to be estimated. We can interpret k_0 as log of prior standard deviation at the beginning of the pre-estimation sample when the user has no cumulative prior experience. That is, $k_0 = \ln\sigma_{M_0}$. Equation (12) shows that the initial uncertainty about activity *j* is less if a user had engaged in content activity *j* more during the pre-estimation period by reducing its prior variance from $\sigma_{M_0}^2$ to $\sigma_{M_{ij,0}}^2$. Therefore, we expect the sign of the estimate of k_1 to be positive.

3.4. Users' Dynamic Optimization Problem

(a) State Variables

State variables completely summarize all information from the past that is needed for the forward-looking optimization problem (Adda and Cooper, 2003). In our dynamic structural model, there are five kinds of state variables, I_{it}. Note that users can observe these state variables on day *t* before they make content choice decisions for day *t*. The first is user *i*'s day *t* priors for perceived match value from choosing activity *j*, denoted as $\mu_{ij,t}$. The second is user *i*'s day *t* priors for variance of perceived match value from choosing activity *j*, denoted as $\sigma_{Q_{ij,t}}^2$. The third is the count of number of times that user *i* has chosen activity *j* up to day *t*. This is given as follows:

$$l_{ij,t} = \sum_{\tau=1}^{t-1} N_{Eij\tau}. \tag{13}$$

The fourth is the count of number of times that network neighbors of user *i* have chosen activity *j* up to and through day *t*, weighted by the frequency of communication. This is given as follows:

$$m_{ij,t} = \sum_{\tau=1}^{t} N_{WOMij\tau}. \tag{14}$$

Finally, we have the idiosyncratic errors denoted by ε_{ijt}.

(b) Dynamic Decision-Making

A user's optimal decision rule is to choose the option that maximizes the expected present value of utility over the planning horizon. This leads to a dynamic programming problem. One can apply the Bellman's principle to solve this problem by recursively finding value functions corresponding to each alternative choice. Based on the Bellman's equation, we evaluate the value function in the infinite-horizon setting, given as follows:

$$V_{it}(I_{it}) = \max_{j} E\left[U_{ijt} + \beta * E\left[V_{it}(I_{it+1}) | d_{ijt}, M_{Eijt}, M_{WOMijt}, N_{WOMijt}\right] | I_{it}\right] \tag{15}$$

where β is a discount factor. Hence, the optimal decision rule is $\text{argmax}_j\{V_{ijt}(I_{it})\}$ where, for every *j*,

$$V_{ijt}(I_{it}) = E\left[U_{ijt} | I_{it}\right] + \beta * E\left[V_{it}(I_{it+1}) | d_{ijt}, M_{Eijt}, M_{WOMijt}, N_{WOMijt}, I_{it}\right] \tag{16}$$

is the choice-specific value function.

Recall that signals received by users are random variables and these are only observable to the users but unobservable to researchers. In order to derive the value function, we need to eliminate the random component of these signals. The way to do this is to generate a sequence of signals for the current period own experience and for both the direct and indirect experience in the next period. Note that in the above equation we have two components: one outer "expectation" term and the other inner "expectation" term. Hence, towards computing this value function, we take the outer expectation over M_{Eijt}^{s} and the inner expectation over both M_{Eijt+1} and $M_{WOMijt+1}$. We employ a variant of the Keane and Wolpin (1994) approximation method for computing the value function.

(c) Integrated Value Function

The integrated value function is the expectation of the value function over the distribution of unobservable state variables (e.g., ε_{ijt}), conditional on the observable state variables: (for simplicity, we drop out subscripts *it* in $\overline{V}$)

$$\overline{V}(I_{it}) = \int V\left(I_t, \varepsilon_{ijt}\right) dG_{\varepsilon}\left(\varepsilon_{ijt}\right). \tag{17}$$

This function is the unique solution to the integrated Bellman's equation:

$$\overline{V}(I_{it}) = \int \max_j E\{U_{ijt} + \beta * E[\overline{V}(I_{it+1}|d_{ijt}, M_{Eijt}, M_{WOMijt}, N_{WOMijt})]|I_{it}\} dG_\varepsilon(\varepsilon_{ijt}). \tag{18}$$

Hence, the choice-specific value function becomes:

$$V_{ijt} = E[U_{ijt}|I_{it}] + \beta * E[\overline{V}_{it}(I_{it+1})|d_{ijt}, M_{Eijt}, M_{WOMijt}, N_{WOMijt}, E[U_{ijt}|I_{it}]]. \tag{19}$$

We use this choice-specific value function with the integrated value function to compute the choice probability. We will explain this in the estimation section. Note that if ε_{ijt} are i.i.d. type-1 extreme value random variables, this becomes the dynamic problem conditional on logit model with Bellman's equation:

$$\overline{V}(I_{it}) = \log\Bigg(\sum_{j=1}^{4} \exp\Big\{w_g * \mu_{ij,t} + w_g * r_g * (\mu_{ij,t})^2 + w_g * r_g * \sigma^2_{M_{ij,t}} + w_g * r_g * \sigma^2_\eta - \alpha_g * p_j$$
$$+\beta * E[\overline{V}(I_{it+1})|d_{ijt}, M_{Eijt}, M_{WOMijt}, N_{WOMijt}]\,|I_{it}\Big\}$$
$$+\exp\{\Phi_0 + \beta * E[\overline{V}(I_{it+1})|d_{ijt}, M_{Eijt}, M_{WOMijt}, N_{WOMijt}]\,|I_{it}\}\Bigg). \tag{20}$$

Note that the idiosyncratic error term is integrated out. We can also interpret the value from the integrated value function as "inclusive value" for deciding which activity to engage in conditional on a set of state variables. Also, note that the last additive term represents the utility from the fifth option, "doing nothing" and we integrate out the indirect experience signals.

3.5 Estimation

We start by outlining the choice probabilities and the likelihood function. Then we discuss the estimation procedure followed by a discussion of our identification restrictions.

(a) Choice Probability

Let Φ_g denote the complete set of model parameters for a user of latent class g. We define the deterministic part of the choice-specific value function is as following (for simplicity, we drop the superscript *s* denoting the *s*[th] event):

$$V_{ijt}(I_{it}|\Phi_g) = V^*_{ijt}(I_{it}|\Phi_g) - \varepsilon_{ijt}. \tag{21}$$

If ε^s_{ijt} are i.i.d. type-1 extreme value random variables, the probability of user *i* doing activity *j* at time *t* is given by:

$$\mathrm{Prob}\left(d_{ijt}=1|I_{it},\Phi_g\right)=\frac{\exp\left\{V_{ijt}\left(I_{it}|\Phi_g\right)\right\}}{\sum_{h=1,5}\exp\left\{V_{iht}\left(I_{it}|\Phi_g\right)\right\}}. \tag{22}$$

(b) Likelihood Functions

Let $H_i=\left\{\left\{\left\{d^s_{ijt}\right\}_{j=1}^{5}\right\}_{s=1}^{N_{Eijt}}\right\}_{t=1}^{T}$ denote user *i*'s choice history, where *T* is the last observation period. Recall that we have five options ranging from 1 (upload to SNC sites) to 5 (doing nothing). Then,

$$\mathrm{Prob}\left(H_i|\Phi_g\right)=\prod_{t=1}^{T}\prod_{s=1}^{N_{Eijt}}\prod_{j=1}^{5}\mathrm{Prob}\left(d^s_{ijt}=1|I_{it},\Phi_g\right)^{d^s_{ijt}}. \tag{23}$$

Also, let $\tilde{\zeta}_{it}=\left\{\left\{\left\{d^s_{ijt}\zeta^s_{ijt}\right\}_{j=1}^{4}\right\}_{s=1}^{N_{Eijt}}\right\}_{t=1}^{t}$ and $\tilde{\eta}_{it}=\left\{\left\{\left\{\sum_{s=1}^{N_{Ekjt}}\left(w_{ik}d^s_{kjt}\right)\eta^s_{kjt}\right\}_{k\in n_i}\right\}_{j=1}^{4}\right\}_{t=1}^{t}$ denote the sets of direct experience signals and indirect WOM signals, respectively, received by user *i* up to and through time *t*, such that $I_{it}=I_{it}\left(\tilde{\zeta}_{it},\tilde{\eta}_{it}\right)$. Then we can write the probability of observed history of user *i* as follows:

$$\int_{\tilde{\zeta}_{ijt}}\int_{\tilde{\eta}_{ijt}}\prod_{t=1}^{T}\prod_{s=1}^{N_{Eijt}}\prod_{j=1}^{5}\mathrm{Prob}\left(d^s_{ijt}=1|I_{it}\left(\tilde{\zeta}_{it},\tilde{\eta}_{it}\right),\Phi_g\right)^{d^s_{ijt}}dF\left(\tilde{\zeta}_{it},\tilde{\eta}_{it}\right). \tag{24}$$

Finally, let $\tilde{x}_{it}=\left\{\left\{x_{ij}\right\}_{j=1}^{4}\right\}$ denote a set of hypothetical content match value signals with variance $\sigma^2_{xij}=\left[1/\sigma^2_{M_{ij,0}}-1/\sigma^2_{M_0}\right]^{-1}$. We can think of the user as receiving one cumulative signal that results in this decrease in variance (that is, an increase in signal accuracy). Thus, as shown in Erdem et al. (2006) and Mehta et al. (2008), we represent this cumulative signal as follows:

$$x_{ij}\sim N\left(M_{ij},\sigma^2_{xij}\right). \tag{25}$$

Note that we use M_{ij} as a mean rather than M_j. Thus, given the cumulative signal in Equation (25) and the user's prior mean belief about content activity *j* at the beginning of the pre-estimation sample, we can calculate the mean match value belief at the end of the pre-estimation sample using Bayesian updating formula as follows:

$$\mu_{ij,0} = \begin{cases} \dfrac{M_0/\sigma^2_{M_0} + x_{ij}/\sigma^2_{xij}}{1/\sigma^2_{M_0} + 1/\sigma^2_{xij}}, & \text{if user i has at least one prior experience of activity j,} \\ M_0, & \text{otherwise.} \end{cases} \quad (26)$$

We use $\mu_{ij,0}$ as the initial mean match value belief for user *i* for content activity *j* at the beginning of the estimation sample.

(c) Simulation Estimation

We adopt the simulated maximum likelihood estimation (see Stern 2000). We integrate over direct signals, indirect signals, and initial conditions as follows: Let $(\tilde{\zeta}^u_{it}, \tilde{\eta}^u_{it}, \tilde{x}^u_{it})$ denote the *u*th draw for user *i*, where *u* = 1,..., *U*, we have an unbiased and consistent simulator:

$$\widehat{\text{Prob}}(H_i|\Phi_g) = \frac{1}{U}\sum_{u=1}^{U}\prod_{t=1}^{T}\prod_{s=1}^{N_{Eijt}}\prod_{j=1}^{5}\text{Prob}\left(d^s_{ijt} = 1|I_{it}(\tilde{\zeta}^u_{it}, \tilde{\eta}^u_{it}, \tilde{x}^u_{it}), \Phi_g\right)^{d^s_{ijt}}. \quad (27)$$

Then the simulated likelihood for the sample is:

$$\prod_{i=1}^{N}\sum_{g}\pi_g * \widehat{\text{Prob}}(H_i|\Phi_g). \quad (28)$$

In finding the maximums of the simulated likelihood for the sample, we adopt the quasi-Newton methods. To be specific, we use the BHHH numerical maximization, which makes use of the outer product of the gradients (see Berndt et al. 1974). In addition, we obtain consistent estimates of the variance of $\hat{\Xi}_g$ using the outer product of gradients variance estimator. In sum, we solve a dynamic optimization problem and estimate the simulated likelihood function recursively.[6]

(d) Identification

We briefly discuss identification issues in our model mathematically and empirically. First, we impose a scale normalization restriction by setting for the mean match value of any one activity to be 1. This is because one can scale all the M_j by a positive constant κ, while scaling all the $\sigma_{\zeta j}$ and $\sigma_{\eta j}$ by κ, without changing the choices implied by the model. The mean match value of uploads to SNC sites is set to 1 ($M_3 = 1$) while other activities' qualities are measured relative to SNC uploads. This normalization

[6] We adopt our overall estimation strategy from the nested fixed point algorithm (NFXP) to obtain the maximum likelihood estimator of the structural parameters (see Aguirregabiria and Mira 2009 for detail).

is in the spirit of Erdem et al. (2008) and ensures identification of the mean match value levels associated with each activity.

We can identify k_0 and k_1 from the dynamics of the model. Consider a subset of users with sufficient prior experience of all mobile content activities such that $\sigma_{M_{ij,0}} = 0$. This implies that these users have no uncertainty about content features. In this case, our model would reduce to a static model without learning. In our data, there are users not only with sufficient prior experience, but also users with limited prior experience. This variation across users helps us identify the parameter, k_0 and k_1. Further, the parameters, w and α, are identified by stationary choices from users with sufficient experience in engaging in various content activities, as discussed in Erdem et al. (2008). Note that the location normalization like setting $\varphi_0 = 0$ is not required in our dynamic structural model.[7]

The identification of the risk aversion parameter, r, depends on the dynamics of our model. This is because only when users face uncertainty about content features like in our dynamic learning setting, do they reveal the risk preference (i.e., risk aversion) in their choices. Our panel data satisfies this condition.

The parameters representing the dispersion of the direct and the indirect information signals, $\sigma_{\zeta j}$ and $\sigma_{\eta j}$, are identified by the extent to which users in our sample update their choice probabilities after receiving each type of signal. In addition, we separate the impact of *direct experience* from the impact of *indirect experience* on a user's learning process with respect to content match value with each activity. The main identification restriction is that the direct experience from own usage and generation behaviors impacts a user's utility whereas indirect experience from the usage and generation behaviors of network neighbors influence the kinds of experience signals received but does not impact the utility function of the user directly. This is consistent with the approach of Crawford and Shum (2005). In this sense, we are fortunate in that our data includes instances where users have either zero or little direct experience or where users have zero or little indirect experience from their social network. Moreover, there is a lot of variation in the data in terms of how different users engage in each of the four different kinds of activity (see Figures 1 and 2 and our discussion of empirical identification in Section 4). Each of these unique attributes of our data is useful because variation in the mix of direct and indirect experiences both within and across users is important for identifying the parameters related to the perceived content match value with each activity (or content quality associated with each activity).

Finally, note that prices are not endogenous in our model. This is because prices charged by the mobile phone operator does not vary by content type (whether it is from SNC websites or from mobile portal sites) or by activity (upload or download). The charges incurred by a user are simply based on the number of bytes that are transmitted or received. Therefore, we can treat prices as pre-determined.

[7] Erdem et al. (2008) elaborate on this in great detail in their Online Appendix.

4. Data Description

Our data is drawn from 3G mobile users in Korea who used the services of the company between March 15, 2008 and June 15, 2008. 3G mobile services enable users to upload their content faster than conventional mobile services. Further, these services are more commonly available in the large screen handsets that facilitate more user-friendly content generation and usage compared to the small-screen devices. The dataset that we employ in our analysis consists of 70,923 mobile data transaction records encompassing 500 users' content uploading and downloading behaviors over the 3-month period. We also have data on voice calls made by the same users that enables us to construct their social networks. For these social network neighbors, we have mobile data transaction records. We randomly selected 250 users for calibration and 250 users for validation. Because the data are collected on a daily basis over a 3-month period, the calibration and validation samples consist of 35,047 and 35,876 observations, respectively.

As briefly outlined in the introduction, there are two broad categories of websites users can access through their mobile phone, either for uploading content or for downloading content. The first category is one consisting of regular social networking and community websites that any user can browse through a PC or laptop. Examples of such websites in our data include Cyworld and Facebook. By forcing these off-portal sites to comply with mobile web standards, mobile operators try to ensure visitors a consistent and optimized experience on their mobile device. The second category of websites includes portal sites specifically created by the mobile phone company. Examples of such websites in our data include Nate Portal and KTF Portal, which are the Asian equivalent of US sites like Vodafone live and T-Mobile's Web 'n' Walk. The content on these sites can be accessed through a mobile phone by users who subscribe to the services of the mobile operator. These mobile portals are community-oriented sites that allow users to download and upload (in order to share with others) ringtones, wallpapers, videos, screen savers, video games, etc. Users pay transmission charges for every upload and download, just as they would have to do when accessing the regular Internet sites. The transmission charges are in general the same, irrespective of whether users upload or download content.

We have precise transmission data and time stamp information from individual-specific transactions that involve either an upload or download of content. Table 2 shows summary statistics of our data. The first interesting observation is that users are more actively engaged in content usage instead of content creation. This suggests that most users' content creation activities are still in a nascent stage. Further, their content usage activities primarily focus on content download from mobile portals. Hence, users may engage in experimentation through content creation in order to learn about its benefits. This helps us capture users' dynamic learning behavior in the mobile media setting.

As noted before, there are two *sources* of learning in our setting. First, users can learn through their own usage over time. We refer to this as *direct experience*. Second, users can learn from the behavior of their social networks (i.e., some kind of a word of mouth from their network neighbors). We refer to this as word-of-mouth (WOM) or *indirect experience*. In our model and data, the extent of such indirect learning can be adjusted by communication strength (i.e., call frequency or call duration). We have tried both combinations and found that the qualitative nature of the results remain unchanged.

In addition, there are two kinds of content-specific learning. The first is when users learn about their "match value" or "taste" for different kinds of content-related activities. This is based on the notion that some content (like ringtones or video games) could be horizontally differentiated and hence, such content may be more appealing to distinct user groups than others. For instance, younger users are more likely to engage in uploading content to SNC sites since they care about their reputation and popularity on these sites. In contrast, older users are more likely to engage in content download from mobile portal sites since they care more about applications they can use in their professional lives such as podcasts. Indeed, anecdotal reports in the trade press suggest that there is evidence about this kind of behavior. The second is when users learn about the "true quality" of content associated with each of the four activities. This is based on the notion that some multi-media content (such as video files) could be vertically differentiated where all users agree on the quality-levels of different types of content.

Table 2. Summary Statistics

Variable	Mean	Std. Dev	Min	Max
Direct Experience				
Frequency of activity 1: content upload to the SNC sites	0.039	0.644	0	33
Frequency of activity 2: content upload to the mobile portal site	0.013	0.138	0	4
Frequency of activity 3: content download from the SNC sites	0.008	0.042	0	3
Frequency of activity 4: content download from the mobile portal site	1.965	6.779	0	472
Indirect Experience				
Frequency of activity 1: content upload to the SNC sites	0.007	0.128	0	7.829
Frequency of activity 2: content upload to the mobile portal site	0.005	0.152	0	14.171
Frequency of activity 3: content download from the SNC sites	0.001	0.062	0	7.829
Frequency of activity 4: content download from the mobile portal site	1.216	8.604	0	267.2

Notes*: Frequency is the count of number of non-zero packet transmission for each activity across all users computed on a daily basis. The frequency of indirect WOM experience is a weighted average of the number of times the network neighbors of a given user have engaged in a given activity on a given day. Hence, it may exceed 1.*

Table 3. Matrix Highlighting Conditional Switching Probability Between Activities

Prob(Current Activity | Previous Activity) in %		Time t+1				
		Activity 1	**Activity 2**	**Activity 3**	**Activity 4**	**Activity 5**
Time t	**Activity 1**	47.2	0.0	2.8	44.4	5.6
	Activity 2	0.0	21.2	0.0	51.5	27.3
	Activity 3	16.7	0.0	16. 7	50.0	16. 7
	Activity 4	0.2	0.3	0.0	94.3	5.1
	Activity 5	0.1	0.3	0.0	8.4	91.2

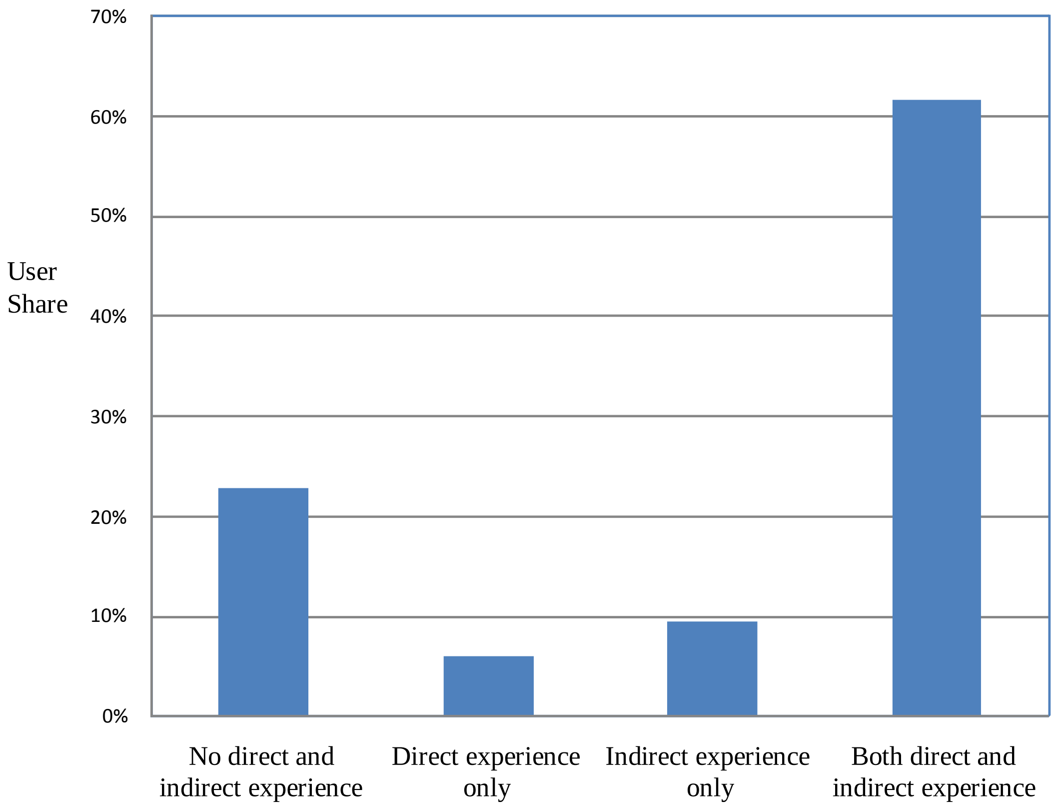
Notes: *Activity 1-5 denote uploading content to SNC sites, upload contenting to the mobile portal sites, downloading content from SNC sites, downloading content from the mobile portal sites, and doing nothing, respectively.*

Our main model is based on the first kind of learning that is, learning about the match value of content associated with each of the four kinds of activities. As an extension, we also model and estimate parameters for the second kind of learning (about true quality of content associated with each activity). The details of the model extension are given in the Appendix.

In addition, since we do not observe when users actually began their first downloading or uploading activity since the inception of the service, there could be potential initial condition or left-censoring problems. To alleviate such issues, we use a 8-week pre-estimation data of users' content-related activities to model prior beliefs about mean and variance of match values at the beginning of the estimation period.

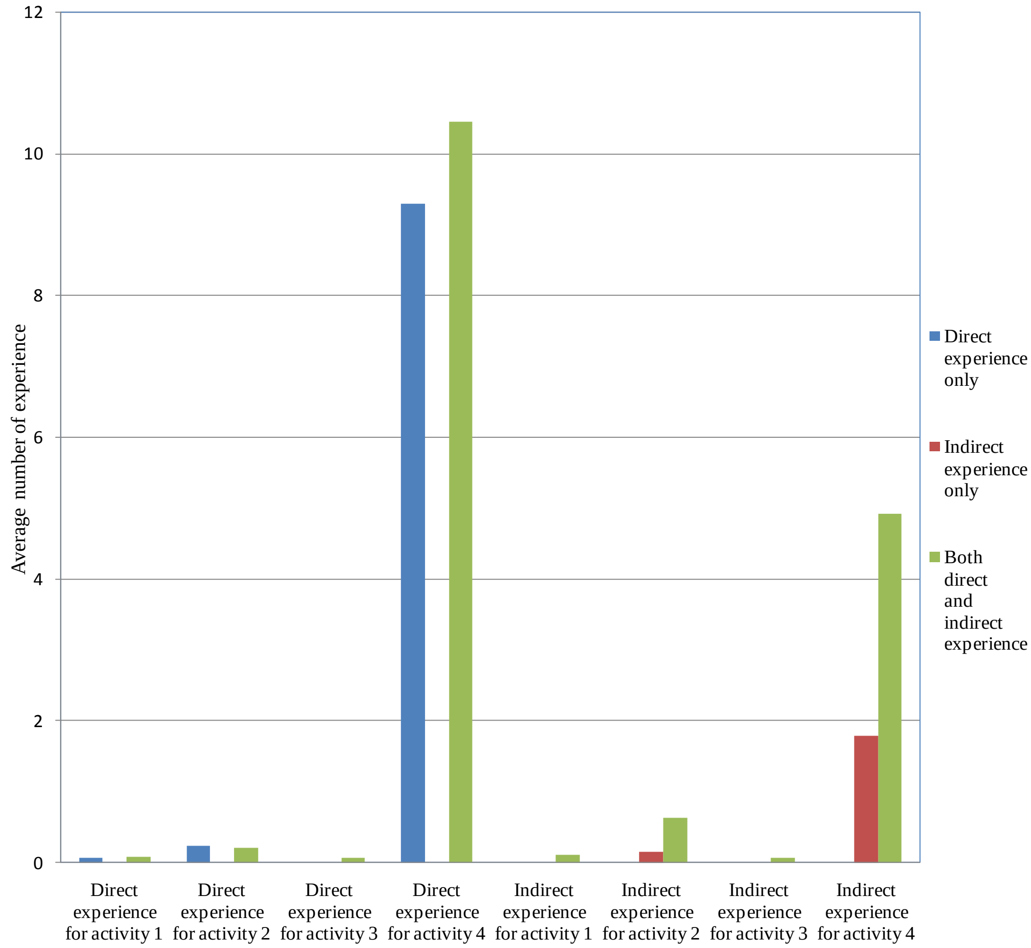
We next present some suggestive evidence of learning through users' conditional switching propensities across the five options available to them in Table 3. First, these probabilities suggest that some activities tend to elicit a relatively higher probability of switching (activities 1, 2 and 3) while other activities tend to elicit a relatively lower probability of switching (activities 4 and 5). For any given activity, this phenomenon is evident from comparing the off-diagonal elements with the diagonal elements. Interestingly, we find that for the various activities there are non-zero probabilities of users switching to other activities across adjacent time periods. The off-diagonal elements are quite different from zero for activities 1 to 3. Even for activities 4 and 5, we see that there is a non-trivial probability of users switching from these activities to other activities, 1-3. Recall that activities 1 through 4 denote content upload to SNC websites, upload to mobile portal sites, download from the SNC websites and download from mobile portal sites. The first three of these are relatively recent service features enabled in the mobile setting, as opposed to content download from mobile portal sites, which has existed for a much longer time period. This indicates that to some extent users often engage in new types of content usage and creation, further suggesting the experimental nature of their content-related activities. These descriptive statistics motivate further examination of exactly how the learning process works in this setting.

Figure 1. Plot Showing Variation in Users' Experiences



In addition, our data presents evidence of empirically identifying the impact of *direct experience* from the impact of *indirect experience* on a user's learning process with respect to content match value. Figure 1 shows that a large proportion of users (62%) experience both direct and indirect signals. However, there also exist users who have either very little direct or very little indirect experience (6% and 10%, respectively). Further, Figure 2 shows that for each activity, there exist a great deal of variation in the average number of experiences per user across each of the two sources of learning. For example, with respect to activity 4, instances of *direct* experience are observed for users who belong to either the "direct only" experience or "both direct and indirect" experience categories, or both. In contrast, for the same activity, instances of *indirect* experience are observed for those users who belong to either the "indirect only" experience or "both direct and indirect" experience categories, or both. In a similar vein, for activity 2, more instances of *direct* experience are observed for those users who belong to the "direct only" category. In contrast, more instances of *indirect* experience are observed for those users who belong to the "both direct and indirect" category. Thus, we can see that due to significant amount of variation in the data, the impact of direct experience is identified by the extent of variation in the activities of users who only have direct experiences, whereas the impact of indirect experience is identified by the extent of variation in the users who only have indirect experiences from their social networks.

Figure 2. Variation in Experience by User, Activity, and Source



5. Empirical Results

5.1 Goodness of Fit Tests

Our model allows for user heterogeneity in the match value weight (w_g), risk coefficient (r_g), and price coefficient (a_g). Hence, we first choose the number of latent classes, g. We report goodness of fit criteria for models with 1 and 2 latent classes in Tables 4a and 4b. We calculate the log likelihood, the AIC and the BIC for both models in the estimation sample, and we compute the log likelihood in the holdout sample.[8] As we know, the model with the lower value of AIC and BIC is preferred. Increasing the number of latent classes (g) from one to two improves AIC and BIC in Model 1 (content match value

[8] The AIC and the BIC are given as $-2 \ln (L) + 2k$ and $-2 \ln (L) + k \ln(n)$, respectively, where L is the likelihood, k is the number of parameters, and n is the sample size.

model). Thus, we select the two latent class specification in the content match value model.[9] We note that we also did the fit comparison with a modified version of the model specification (Model 2) as shown in the Appendix (whose parameters are shown in Table 7). Similarly, we select the two latent class model in the content true quality model. Further, we find that our proposed main model with content match value does better than alternative model with content true quality value (AIC of 55902.8 vs. 58131.6 in the two-latent class case). A similar trend can be seen from the comparison of the BIC results.

Table 4a. Selection Criteria Comparison for Content Match Value Model (Model 1)

	One latent class	Two latent classes
Log likelihood	-28108.1	-27926.4
AIC	56258.2	**55902.8**
BIC	56435.9	**56114.4**
Num. of parameters	21	25
Sample size	35047	35047

Table 4b. Selection Criteria Comparison for Content True Quality Model (Model 2)

	One latent class	Two latent classes
Log likelihood	-29171.4	-29044.8
AIC	58376.8	**58131.6**
BIC	58520.7	**58309.3**
Num. of parameters	17	21
Sample size	35047	35047

To further validate these results in a holdout sample, we implement a comparison of choice frequencies between sample data and simulated data from models. The usage share comparison between sample data and simulated data from models in Table 5 shows the content match value model (Model 1) fits the data slightly better than the true content quality model (Model 2).

In sum, based on results from in-sample fitness comparison, we decided to use two latent class model and found that Model 1 slightly outperforms Model 2. In addition, based on out-of-sample prediction comparison, we found the same result. Therefore, we decided to use two latent class content match value models for further analysis using policy simulations.

[9] We estimated the model with 3 latent class specification, but found that increasing from 2 latent classes to 3 latent classes deteriorates BIC. Therefore, we finally select the 2 latent class specification for the true content quality model. We do not report the estimates and the fitness criteria for the 3 latent class model only due to brevity.

Table 5. Usage Share Comparison Between Simulated and Sample Data

Activity	Usage Share Comparison		
	Holdout Sample	Simulated Data Model 1 (match value)	Simulated Data Model 2 (true quality)
1: uploading to SNC sites	0.09%	0.42%	0.04%
2: uploading to portal sites	0.39%	0.59%	0.44%
3: downloading from SNC sites	0.04%	0.00%	0.00%
4: downloading from portal sites	83.77%	83.89%	85.07%
5: doing nothing	15.71%	15.11%	14.45%

5.2 Parameter Estimates

The results of the parameter estimates for the content match value model are shown in Table 6. We find that there is substantial difference in the mean match values across different content types. Downloads from mobile portal sites have the highest mean match value level, followed by upload to mobile portal sites, upload to SNC sites and download from SNC sites. Whereas, the extent of heterogeneity in the content match values is invariant by different content types. In addition, we find that consumers are significantly risk averse in this category ($r = -0.035$ for 1st latent class and -0.036 for the 2nd latent class). This is consistent with prior literature (Erdem and Keane 1996), which has also emphasized the importance of controlling for risk aversion to obtain unbiased estimates of advertising effects.

With respect to direct experience, signals about the match value with content download from SNC sites are the most accurate, whereas signals about the content download from mobile portal sites are the least accurate direct experience signals. Interestingly, the magnitude of the standard deviation (accuracy) of direct experience signal is (inversely) proportional to the associated content mean match value. This indicates that a content with higher match value may also invite a higher amount of usage. Hence, we expect the higher volume of the direct experience to be associated with the greater variation of users' match value with the content activity.

In addition, with respect to indirect experience, we find that signals about the match value with upload to SNC sites are the most accurate, whereas signals about the match value with download from SNC sites are the least accurate. In terms of magnitude of estimates, we note that the standard deviation of indirect experience signals is higher than the standard deviation of direct experience signals. This is consistent with what one would expect - learning based on direct experience is more reliable (has less variability) than learning based on indirect experience because the information signals of neighbors may be not fully observed by or communicated to a user.

Table 6. Parameter Estimates (Content Match Value Model)

Parameters that differ by user segment		**Segment 1**		**Segment 2**	
		Estimate	**Std. error**	**Estimate**	**Std. error**
Utility function					
w	Match value coefficient	2.197	1.17E-4***	2.196	1.18E-4***
r	Risk-aversion coefficient	-0.035	1.15E-4***	-0.036	1.16E-4***
α	Price coefficient	0.450	1.17E-4***	0.452	1.16E-4***
π	Segment membership probability	0.526	7.00E-4***	0.474	-
Homogenous parameters				**Estimate**	**Std. error**
Match Value					
M_1	Mean match value of uploading to SNC sites			1.124	1.11E-4***
M_2	Mean match value of uploading to portal sites			1.327	1.16E-4***
M_3	Mean match value of downloading from SNC sites			1	-
M_4	Mean match value of downloading from portal sites			1.834	1.19E-4***
σ_{M1}	Std. dev. of match value of uploading to SNC sites			0.110	7.00E-4***
σ_{M2}	Std. dev. of match value of uploading to portal sites			0.086	7.11E-4***
σ_{M3}	Std. dev. of match value of downloading from SNC sites			0.085	7.01E-4***
σ_{M4}	Std. dev. of match value of downloading from portal sites			0.083	7.35E-4***
φ_0	Constant utility from doing nothing			3.249	1.18E-4***
Signals					
$\sigma_{\zeta 1}$	Std. dev. of direct signal of uploading to SNC sites			0.054	1.27E-4***
$\sigma_{\zeta 2}$	Std. dev. of direct signal of uploading to portal sites			0.091	1.26E-4***
$\sigma_{\zeta 3}$	Std. dev. of direct signal of downloading from SNC sites			0.024	1.35E-4***
$\sigma_{\zeta 4}$	Std. dev. of direct signal of downloading from portal sites			0.197	1.17E-4***
$\sigma_{\eta 1}$	Std. dev. of indirect signal of uploading to SNC sites			0.217	1.16E-4***
$\sigma_{\eta 2}$	Std. dev. of indirect signal of uploading to portal sites			0.325	1.20E-4***
$\sigma_{\eta 3}$	Std. dev. of indirect signal of downloading from SNC sites			0.374	1.19E-4***
$\sigma_{\eta 4}$	Std. dev. of indirect signal of downloading from portal sites			0.332	1.23E-4***
Initial conditions					
k0	Initial condition parameter 1			1.919	1.83E-4***
k1	Initial condition parameter 2			0.048	1.81E-4***

Notes: *Activity 1-4 denote uploading content to SNC sites, upload contenting to the mobile portal sites, downloading content from SNC sites, and downloading content from the mobile portal sites, respectively. *** denotes significant at 0.01. E-4 denotes* 10^{-4}.

We next present the parameter estimates from an extension of the content match value model. We consider an alternative setting where certain content characteristics may have more appeal to distinct user groups. In this setting, user *i* has an idiosyncratic match value with content activity *j*. These estimates are given in Table 7. The qualitative nature of the estimates is the same as in Table 6. For details of the content true quality model, refer to the Appendix A.

Table 7. Parameter Estimates (True Content Quality Model)

Parameters that differ by user segment		**Segment 1**		**Segment 2**	
		Estimate	**Std. error**	**Estimate**	**Std. error**
Utility function					
w	Quality coefficient	2.187	1.80E-4***	2.188	1.84E-4***
r	Risk-aversion coefficient	-0.032	1.84E-5***	-0.035	1.83E-5***
α	Price coefficient	0.451	9.20E-5***	0.457	9.20E-5***
π	Segment membership probability	0.495	1.82E-4***	0.505	-
Homogenous parameters				**Estimate**	**Std. error**
Quality					
Q_1	Quality level of activity 1			1.122	9.07E-5***
Q_2	Quality level of activity 2			1.323	9.08E-5***
Q_3	Quality level of activity 3			1	-
Q_4	Quality level of activity 4			1.828	9.08E-5***
φ_0	Constant utility from doing nothing			3.197	1.83E-4***
Signals					
$\sigma_{\xi 1}$	Std. dev. of direct experience signal of activity 1			0.054	1.81E-5***
$\sigma_{\xi 2}$	Std. dev. of direct experience signal of activity 2			0.090	1.83E-5***
$\sigma_{\xi 3}$	Std. dev. of direct experience signal of activity 3			0.026	1.84E-5***
$\sigma_{\xi 4}$	Std. dev. of direct experience signal of activity 4			0.209	9.14E-5***
$\sigma_{\delta 1}$	Std. dev. of indirect experience signal of activity 1			0.195	9.16E-5***
$\sigma_{\delta 2}$	Std. dev. of indirect experience signal of activity 2			0.324	9.20E-5***
$\sigma_{\delta 3}$	Std. dev. of indirect experience signal of activity 3			0.377	9.19E-5***
$\sigma_{\delta 4}$	Std. dev. of indirect experience signal of activity 4			0.330	9.23E-5***
Initial conditions					
k0	Initial condition parameter 1			1.922	1.83E-4***
k1	Initial condition parameter 2			0.045	1.81E-5***

Notes: *Activity 1-4 denote uploading content to SNC sites, upload contenting to the mobile portal sites, downloading content from SNC sites, and downloading content from the mobile portal sites, respectively. *** denotes significant at 0.01. E-4 denotes 10^{-4}.*

6. Policy Simulations

We next use our estimates to assess the importance of uncertainty, learning, and experimentation in generating the content upload and download sequences observed in the data. To assess the extent of learning, we simulate 35,876 upload and download sequences for randomly drawn 250 users under different counterfactual assumptions, where the population mean content match value, the degree of heterogeneity in individual match value, the accuracy of direct and indirect signals, and their combinations are modified.

One of key decisions for mobile phone operators is to select the third-party mobile content providers who are responsible for aggregating and providing various kinds of multi-media content on the mobile portal sites. As in any business situation, higher the content match value provided in mobile portal sites, higher the costs incurred by mobile content providers. The benefits from high content match value provision include increased content usage by the users of the mobile service. Content is often dynamically tailored to subscribers according to factors such as demographics, device capabilities and subscriber profile. These practices can lead to higher customer satisfaction in the short term and has long term implications for revenue generation and content monetization by targeted advertising. Therefore, operators need to invest time and effort in the selection of mobile content providers.[10] In addition, they also spend resources in changing user perception of their mobile content by advertising in other, more traditional media. These efforts by the company need to be adjusted by varying needs from the heterogeneous users. Hence, mobile phone companies are interested in understanding the effect of changes in user perceptions about the match value with their content as well as the actual experience signals (from both direct and indirect sources) on user upload and download behavior. Accordingly, we run policy simulations to tease out these insights. In next section, we report the policy simulation results from the content match value model, because results from the content true quality model have the same qualitative nature.

6.1 Changes in Population Mean Match Value

Table 8 reports simulated choice frequencies of users where the level of the population mean match value for each content activity increased by 20% although our results are not sensitive to this particular value. As expected, increasing population mean match value generally improves the usage share of all mobile content activities and diminishes frequency of option 5 (doing nothing). The magnitude of the increase of usage share in percentage is the highest for content upload to mobile portal sites as the usage share increases by 21 times from 0.59% to 12.51%, and is the lowest for content download from SNC sites as the usage share remains the same.

Table 8. Changes in Usage Share from 20% Increase in Population Mean Match Value

	Base Case	Impact on activity 1	Impact on activity 2	Impact on activity 3	Impact on activity 4
Upload to SNC sites	0.42%	**5.15%**	0.30%	0.42%	0.00%
Upload to mobile portal sites	0.59%	0.49%	**12.51%**	0.59%	0.00%
Download from SNC sites	0.00%	0.00%	0.00%	**0.00%**	0.00%
Download from mobile portal sites	83.89%	80.87%	75.13%	83.89%	**99.50%**
Doing nothing	15.10%	13.49%	12.06%	15.10%	0.50%

[10] The content usage fee is fairly divided 9:1 between content providers and mobile carriers in Korean mobile industry.

6.2 Changes in Extent of Heterogeneity for Content Match Value

Table 9 and Table 10 report simulated choice frequencies of users where the extent of heterogeneity for content match value with each content activity increased by 20% and decreased by 20%, respectively. The changes in usage share vary by the magnitude of mean population match value of the content activity. Increasing the extent of heterogeneity for content match value improved the usage share in content upload to SNC sites and content upload to mobile portal sites, whose mean match value and observed usage share are low. Whereas, increasing the extent of heterogeneity for content match value reduced the usage share in content download from mobile portal sites, whose mean match value and observed usage share are high. We find the same result but with opposite direction in usage share changes.

In addition, Table 11 reports simulated choice frequencies of users where both the population mean match value and the extent of heterogeneity increased by 20%. As expected, increasing them simultaneously significantly improved the usage share in all content activities. However, in the case of content upload to SNC sites and content upload to mobile portal sites, the magnitude of the increase in usage share was substantially larger than the sum of the increases when we increased the mean match value and the extent of heterogeneity separately. That is, in the content upload to SNC sites, 6.06 percentage point increase from 0.42% to 6.48% was higher than the sum of 4.73 percentage point increase from 0.42% to 5.15% and 0.32 percentage increase from 0.42% to 0.74%. We find a similar result for the content upload to mobile portal sites. These results suggest that the mean match value and the user taste heterogeneity can act as complements in content activities involving content upload to SNC sites and content upload to mobile portal sites.

Table 9. Changes in Usage Share from 20% Increase in Taste Heterogeneity in Match Value

	Base Case	Impact on activity 1	Impact on activity 2	Impact on activity 3	Impact on activity 4
Upload to SNC sites	0.42%	**0.74%**	0.42%	0.42%	0.50%
Upload to mobile portal sites	0.59%	0.57%	**0.80%**	0.59%	0.64%
Download from SNC sites	0.00%	0.00%	0.00%	**0.00%**	0.00%
Download from mobile portal sites	83.89%	83.70%	83.72%	83.89%	**82.62%**
Doing nothing	15.10%	14.99%	15.06%	15.10%	16.24%

Table 10. Changes in Usage Share from 20% Decrease in Taste Heterogeneity in Match Value

	Base Case	Impact on activity 1	Impact on activity 2	Impact on activity 3	Impact on activity 4
Upload to SNC sites	0.42%	**0.24%**	0.42%	0.42%	0.35%
Upload to mobile portal sites	0.59%	0.59%	**0.30%**	0.59%	0.55%
Download from SNC sites	0.00%	0.00%	0.00%	**0.00%**	0.00%
Download from mobile portal sites	83.89%	84.00%	84.11%	83.89%	**84.88%**
Doing nothing	15.10%	15.17%	15.17%	15.10%	14.22%

Table 11. Changes in Usage Share from 20% Increase in Both Population Mean Match Value and Taste Heterogeneity in Match Value

	Base Case	Impact on activity 1	Impact on activity 2	Impact on activity 3	Impact on activity 4
Upload to SNC sites	0.42%	**6.48%**	0.31%	0.42%	0.00%
Upload to mobile portal sites	0.59%	0.47%	**13.66%**	0.59%	0.00%
Download from SNC sites	0.00%	0.00%	0.00%	**0.00%**	0.00%
Download from mobile portal sites	83.89%	79.91%	74.11%	83.89%	**99.35%**
Doing nothing	15.10%	13.14%	11.92%	15.10%	0.65%

6.3 Additional Policy Simulations Based on Sample Splits

We conduct additional counterfactuals by separating the holdout sample by age (young vs. old), sex (male vs. female), and geographic mobility (“more mobile” vs. “less mobile”). Thereafter, we alter the level of mean match value. We seek to answer how the changes in the mean match value of a given activity affect its usage share and how that impact varies by user characteristics. As before, for each of the counterfactuals, we increase population mean match value by 20%, although our results are not sensitive to this particular value.

The first panel of Table 12 presents baseline simulated usage share of each content activity as implied by the content match value model. The 2nd and 3rd panels in this table show the usage share by the extent of mobility of users (less mobile vs. mobile). We use the average extent of mobility in the holdout sample as a cutoff value to determine whether a user is less mobile or not. The 4th through 12th panels represent the cases when we increase the population mean match value by 20%.

An interesting finding is that a 20% increase in mean match value for content download from the mobile portal sites (activity 4) improves the usage share for that activity relatively more in the "more mobile" user compared to "less mobile" user group. This indicates that a higher match value leads to increased usage share in the "more mobile" user group than in the "less mobile" user group for content download from the mobile portal sites. In contrast, a 20% increase in mean match value for content upload from the mobile portal sites (activity 4) improves the usage share for that activity relatively more in the "less mobile" user compared to "more mobile" user group.

Table 12. Changes in Usage Share from 20% Increase in Population Mean Match Value by User Mobility Characteristic

Activity	Base Case (%)			Increase in Match Value for Uploading to SNC Sites (%)			Increase in Match Value for Uploading to Portal Sites (%)			Increase in Match Value for Downloading from SNC Sites (%)			Increase in Match Value for Downloading from portal sites(%)		
	All	Less Mobile	More Mobile	All	Less Mobile	More Mobile	All	Less Mobile	More Mobile	All	Less Mobile	More Mobile	All	Less Mobile	More Mobile
1	0.42%	0.00%	0.42%	5.15%	1.27%	3.87%	0.30%	0.00%	0.30%	0.42%	0.00%	0.42%	0.00%	0.00%	0.00%
2	0.59%	**0.12%**	**0.47%**	0.49%	0.10%	0.38%	12.51%	**6.14%**	**6.37%**	0.59%	0.12%	0.47%	0.00%	0.00%	0.00%
3	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
4	83.89%	**53.68%**	**30.21%**	80.87%	52.88%	27.99%	75.13%	49.46%	25.87%	83.89%	53.68%	30.21%	99.50%	**62.23%**	**37.27%**
5	15.10%	8.71%	6.40%	13.50%	8.25%	5.25%	89.08%	7.12%	4.96%	15.10%	8.71%	6.40%	0.50%	0.28%	0.22%

7. Discussion and Implications

In this paper, we present dynamic structural models in which users learn about content match value or content true quality associated with four different activities through two distinct channels: (i) direct experience from own content creation and usage behavior, and (ii) indirect experience from the content creation and usage behavior of social network neighbors. The model is estimated on a dataset consisting of mobile media content usage and creation behavior where we have information on the content upload and download behavior of users from two different categories of websites - Internet social networking and community sites and mobile portal sites.

In the content match value model, we model that users make activity choices based on how well the content related to a given activity matches their taste. Our estimates suggest that when it comes to user learning from direct experience, the content that is downloaded from mobile portal sites exhibits the highest level of mean match value. In contrast to this, content that is downloaded by users from regular

Internet SNC sites exhibits the lowest level of mean match value. This is consistent with the anecdotal fact that content provision to users via mobile portals (which are typically owned and hosted by mobile operators) preceded content provision via Internet SNC websites. In the early stages after the launch of their mobile services, most mobile phone operators implemented "closed" content management systems to exercise control on the kinds and experiences of content that is available to users on their mobile devices. Subsequently, users had access to WAP-enabled regular Internet websites. Hence, the option of accessing third-party content via mobile portal sites was available to users much before the option of accessing multi-media content via regular Internet SNC sites.

Our results can provide some insights for online advertising, given that advertisers are increasingly using the mobile Web as platform to reach users. The total value of advertising on the mobile web was 2.5 billion dollars in 2008. Our results suggest that with regard to embedding advertisements within multi-media content like audio or video files, advertisers would find it more profitable to insert their ads (such as intromercials or rich media ads) within content that is available on mobile portal sites compared to content available regular Internet sites. However, advertisers need to be cautious about the fact that direct user experience suggests content from mobile portal sites has a high variance in match value. To alleviate this they could outsource their mobile content development tasks to high quality third-party content providers. We find qualitatively similar results from the content quality model.

Our policy simulations suggest that content match value and the extent of heterogeneity for match value can act as complements for activities involving uploading content to mobile portal sites or to SNC sites, leading to an increased frequency in each of these activities. Further, the impact of an increase in content match value on the propensity to download content from mobile portal sites is higher for the segment that is geographically more mobile. In contrast, the impact of an increase in content match value on the propensity to upload content to mobile portal sites is higher for the segment that is geographically less mobile. These results give companies some insights into which user segments to target with incentives to contribute high quality content through mobile phones and handheld devices. Firms can incentivize their customers to generate high-quality content by providing them with explicit monetary rewards. For example, firms could design programs or contests that lead to more frequent and high quality user-generated content updates on online social networking sites. In doing so, firms can make high-quality user-generated content available on mobile portal sites and thereby increase its match value.

In addition, increasingly, there are incentives for users to engage in content creation and uploading to mobile portals. Even in the U.S., mobile operators like Cingular offer a "Messaging Awards" program, where customers vote on the best user-generated video, photo and text submissions. From the firms' perspective, mobile carriers are looking to take advantage of user-generated mobile content, given it doesn't cost the carrier anything to create, and motivates the consumer to transmit content over the pipes that is more profitable than the transmission of low-margin voice services. In addition, the lack of a seamless user experience, technical difficulties with uploading and downloading, and privacy-related concerns can hinder users from contributing high-quality content. Thus, firms would also find it useful to address such issues in order to improve the mean match values with content uploading. Additional policy simulations suggest that mobile operators can use the extent of mobility information when they determine who to recommend ads embedded in high-quality content, generated by users.

Our paper has several limitations, which could be avenues for future research. Two in particular are worth some discussion. For example, we do not consider the actual amount of content generation and usage activities in our analysis. Instead, we focus only on frequency of these activities. Second, we do not have information on the specific types of content that are being generated or downloaded (such as audio files or video files) in our data. If one had access to such data, one could build a model that associated specific features of content to the magnitude of the direct and indirect effects. Notwithstanding these limitations, we hope our study paves the way for future research in the area of mobile multi-media usage and commerce.

References

- Ackerberg, D. Empirically Distinguishing Informative and Prestige Effects of Advertising, *RAND Journal of Economics* (32:2), 2001, 316-333.
- Aguirregabiria, V., P. Mira. Dynamic Discrete Choice Structural Modes: A Survey, *Journal of Econometrics,* Forthcoming, 2009.
- Archak, N., A. Ghose, and P. Ipeirotis. Deriving the Pricing Power of Product Features by Mining Consumer Reviews, Working paper, 2008, SSRN.
- Berndt, E.K., B. Hall, R. Hall, J. Hausman. Estimation and Inference in Nonlinear Structural Models, *Annals of Economic and Social Measurement* (3:4), 1974, pp. 653-665.
- Chard, I. Exploiting mobile Web 2.0, 2008. http://www.nccmembership.co.uk/pooled/articles/
- Chevalier, J., D. Mayzlin. The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research* 43(3), 2006, 345-354.
- Ching, A., M. Ishihara. The Effects of Detailing on Prescribing Decisions Under Quality Uncertainty, Working paper, 2009 SSRN.
- Chintagunta, P., T. Erdem, P. Rossi, M. Wedel. Structural Modeling in Marketing: Review and Assessment, *Marketing Science* (25:6), 2006, 604-616.
- Crawford, G., M. Shum. Uncertainty and Learning in Pharmaceutical Demand, *Econometrica* (73:4), 2005, 1137-1173.
- Das, S. R., M. Chen. Yahoo! for Amazon: Sentiment Extraction From Small Talk on the Web. *Management Science* (53:9), 2007, 1375-1388.
- Dellarocas, C., N. Awad, M. Zhang. Exploring the Value of Online Product Reviews in Forecasting Sales: The case of Motion Pictures. *Journal of Interactive Marketing* (21: 4), 2007, 23-45.
- Duan, W., B. Gu, A. Whinston. Do online reviews matter? An Empirical Investigation of Panel Data. *Decision Support Systems,* (45:4), 2008, 1007-1016.
- Erdem, T., M. Keane. Decision-making Under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets, *Marketing Science* (15:1), 1996, 1-20.
- Erdem, T., M. Keane, T. Oncu, J. Strebel. Learning about Computers: An Analysis of Information Search and Technology Choice, *Quantitative Marketing and Economics* (3:3), 2005, 207-246.
- Erdem, T., Keane, M., B. Sun. A Dynamic Model of Brand Choice When Price and Advertising Signal Product Quality, *Marketing Science* (27:6), 2008, 1111-1125.
- Ghose, A., P. Ipeirotis, A. Sundararajan. The Dimensions of Reputation in Electronic Markets, Working paper, 2005, SSRN.
- Ghose, A., P. Ipeirotis. Estimating the Socio-Economic Effect of Reviews: Mining Text and Reviewer Characteristics, Working paper, 2008, SSRN.
- Ghose, A. Internet Exchanges for Used Goods: An Emp**ir**ical Analysis of Trade Patterns and Adverse Selection. *MIS Quarterly*, (33:2), 2009, 263-291.
- Ghose, A., S. Han. An Empirical Analysis of User Content Generation and Usage Behavior in Mobile Digital Media**,** NYU Stern Working Paper Series, 2009.
- Gowrisankaran, G., M. Rysman. Dynamics of Consumer Demand for New Durable Goods, Working paper, 2007, SSRN.
- Hendel, I., A. Nevo. Measuring the Implications of Sales and Consumer Stockpiling Behavior, *Econometrica* (74:6), 2006, 1637-1673.
- Israel, M. Services as Experience Goods: An Empirical Examination of Consumer Learning in Automobile Insurance, *American Economic Review* (95:5), 2005, 1444-1463.

- Iyengar, R., A. Ansari, S. Gupta. A Model of Consumer Learning for Service Quality and Usage, *Journal of Marketing Research* (44:4), 2007, 529-544.
- Iyengar, R., T. Valente, C. Van den Bulte. Opinion Leadership and Social Contagion in New Product Diffusion, working paper, 2008, University of Pennsylvania.
- Keane, M., K. Wolpin. The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence, *Review of Economics and Statistics* (76), 1994, 648-672.
- Manchanda, P., Y. Xie, N. Youn. The Role of Targeted Communication and Contagion in New Product Adoption. *Marketing Science*, (27:6), 2004, 961-976.
- Mehta, N., X. Chen, O. Narasimhan. Informing, Transforming, and Persuading: Disentangling the Multiple Effects of Advertising on Brand Choice Decisions, *Marketing Science*, (27:3), 2008, 334-355.
- Nair, H., P. Manchanda, T. Bhatia. Asymmetric Social Interactions in Physician Prescription Behavior: The Role of Opinion Leaders, forthcoming, *Journal of Marketing Research*, 2008.
- Nam, S., P. Manchanda, P. Chintagunta. The Effects of Service Quality and Word-of-Mouth on Customer Acquisition, Retention and Usage, Working paper, 2006, University of Michigan.
- Narayanan, S., P. Manchanda, P. Chintagunta. Temporal Differences in the Role of Marketing Communication in New Product Categories, *Journal of Marketing Research,* (42:3), 2005, 278-290.
- OPA News. The Mobile Web Offers a Rich Platform for Content and Advertising, Online Publishers Association, March, 2007.
- Stern, S. Simulation-based Inference in Econometrics: Motivation and Methods, in *Simulation-based Inference in Econometrics*, Mariano, R., T. Schuermann, M. J. Weeks (Ed.), Cambridge University Press, Cambridge, United Kingdom, 2000, 9-37.
- Trusov, M., A. Bodapati, R. Bucklin. Your members are also your customers: Marketing for Internet social networks. Working paper, 2008, University of Maryland at College Park.
- Van den Bulte, C., G. Lilien. Medical Innovation Revisited: Social Contagion versus Marketing Effort. *American Journal of Sociology*, 106(5), 2001, 1409-1435.

Appendix A.

Model Extension: Content True Quality Value

We consider an alternative setting where we model user uncertainty about content quality as follows. Users are imperfectly informed and uncertain about the mean attribute levels of each of the four kinds of content, similar in spirit to prior work (Erdem and Keane 1996). User experiences with respect to content quality vary. There could be a number of reasons why user experiences vary. First, in our setting, a user's experience of content quality is very likely to be context dependent. In our mobile context, since users may access mobile services from very diverse locations (e.g., on the road in a bus, car or train, at home, at work, etc.), there could be substantial variation in the perceived quality of the content that is consumed as well content that is created. For example, the extent of wireless bandwidth congestion and the availability of mobile applications can vary significantly by time and location of use. Hence, each direct experience of content usage (downloading) or generation (uploading) provides a noisy but unbiased signal of quality for the different activities. We denote the quality of the direct experience signal received by user *i* about activity *j* at *s*th event on day *t*, $\mathrm{Q}^{\mathrm{s}}_{\mathrm{Eijt}}$, as follows:

$$\mathrm{Q}^{\mathrm{s}}_{\mathrm{Eijt}} = \mathrm{Q}_{\mathrm{j}} + \xi^{\mathrm{s}}_{\mathrm{ijt}} \qquad \text{where} \quad \xi^{\mathrm{s}}_{\mathrm{ijt}} \sim \mathrm{N}\left(0, \sigma^2_{\xi\mathrm{j}}\right). \tag{29}$$

That is, $\mathrm{Q}^{\mathrm{s}}_{\mathrm{Eijt}} \sim \mathrm{N}\left(\mathrm{Q}_{\mathrm{j}}, \sigma^2_{\xi\mathrm{j}}\right)$. Here, Q_{j} and $\sigma^2_{\xi\mathrm{j}}$ are the "latent quality index" and the "choice-specific direct experience variability," respectively, similar in spirit to prior work (Erdem et al. 2008).

In addition to variation in the direct experiences of users, there can be variation in the indirect experiences of users. This can happen because the network neighbors of a user, like the users themselves, receive a noisy signal of content quality from the upload and download activities across both the kinds of websites. Moreover, when the information regarding content quality is transferred via (say) word-of-mouth, there could be additional sources of noises such as incorrect delivery of the information by a sender, misunderstanding by a recipient, etc. Hence, to allow for this possibility, we model the information from network neighbors as providing a noisy but unbiased signal.

A complication arises from the fact that users can receive multiple indirect experience signals on a given day. Instead of specifying each indirect signal that the users receive within a given day, we aggregate all indirect signals within a day into one cumulative indirect signal whose accuracy increases in the number of indirect signals. This is similar in spirit to Mehta et al. (2008). Further, we assume that each indirect experience signal comes only from those network neighbors who have experienced it in that period. We denote the indirect experience signal of user *i* from a network neighbor *k* who has participated in activity *j* at the same time *t* as follows:

$$Q^{f}_{WOMijt} = Q_j + \delta^{f}_{ijt} \tag{30}$$

where

$$\delta^{f}_{ijt} \sim N(0, \sigma^2_{\delta j}),$$

$$f \in N_{WOMijt} = \sum_{k \in n_i} \sum_{f=1}^{N_{Ekjt}} w_{ik} d^{f}_{kjt}.$$

That is, $Q_{WOMijt} \sim N(Q_j, \sigma^2_{\delta j})$. We refer to $\sigma^2_{\delta j}$ as the "choice-specific indirect experience variability." Because own experience is likely to provide a less noisy signal of the quality of a given activity than indirect experience, we expect that $\sigma^2_{\delta j} \geq \sigma^2_{\xi j}$ for each activity *j*.